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# Advancing project-scale health impact modeling for active transportation: A user survey and health impact calculation of 14 US trails

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ABSTRACT

Only 21% of American adults achieve recommended levels of physical activity. Urban trails are popular venues both to engage in recreational physical activities and for active commuting. The Rails-to-Trails Conservancy's Trail Modeling and Assessment Platform (T-MAP) is a multi-year research project to develop data-driven trail planning and management tools.

We surveyed over 3000 trail users on 14 US urban trails. The survey was developed specifically to inform health impact calculation, including items on trail use and other physical activity. We calculate health impacts in terms of six chronic diseases and mortality, and use treatment costs and Value of Statistical Life (VSL) for monetization, respectively.

Regular trail use prevents 36 hospitalizations due to chronic diseases and 182 premature deaths per 100,000 trail users and year, worth $2,1 million in avoided treatment costs and $1,7 billion based on VSL, respectively.

Compared to VSL, avoided treatment costs provide more tangible estimates of health impacts, but challenges with data availability and comparability call for cautious interpretations. Our estimates for chronic disease cases are limited to hospitalization discharges and treatment costs, resulting in considerably lower figures than those for reduction in mortality risk.

Trail users are a highly active population. 40% achieve physical activity recommendations even without trail use, and with trail use, 87% do. Health benefits would be more than double if inactive subjects would take up the same amount of trail use as observed in our sample.



## 1. Introduction

Walking and cycling have enjoyed increasing popularity and interest in recent years, both as sustainable modes of transport and promising sources of exercise. Regular physical activity has been associated with a number of positive health outcomes, such as increase in life expectancy and reduced risks in cardiovascular diseases, diabetes, colon and breast cancer,

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among others (Physical Activity Guidelines Advisory Committee, 2008). Only 21% of American adults currently achieve the recommended levels of 150 min of moderate to vigorous physical activity per week (CDC, 2016a).

Walking and cycling shares for transportation trips remain low in the US, around 10%, compared to other areas of the world, where active modes can reach shares as high as 50% (Buehler et al., 2011; Götschi et al., 2015b). Lack of traffic safety and lack of access to high-quality infrastructure and open spaces are meaningful barriers to increasing walking, and in particular cycling (Buehler et al., 2016). Over the past decades, the establishment of multi-use trails for both pedestrians and cyclists, by a growing number of communities with substantial support by trail advocacy organizations, such as the Rails-to-Trails Conservancy (RTC), has developed into an important tool to provide people with safe and pleasant opportunities to engage in walking, running or cycling, for both recreational and utilitarian purposes.

In 2013 RTC launched a major research initiative to support a more systematic approach to trail development by monitoring and valuing trail activity, the Trail Modeling and Assessment Platform (T-MAP). This initiative included the establishment of a US national network of over 50 automated, continuous trail traffic monitoring stations. In addition, in the summer of 2015 we conducted the first national intercept survey of American trail users. The purpose of T-MAP is to develop new tools for trail planning, such as the network analysis tool described by Lowry et al. (2016) and the trail-user intercept survey described by Cohn et al. (2016), and more generally, to build a substantive evidence base to improve our understanding of trail use (e.g. Lindsey et al., 2016). As such, health impact modeling (i.e. the quantitative assessment of health impacts; independent of, or as part of broader *health impact assessments* (Hebert et al., 2012) is an important element of T-MAP.

Health impact modeling of active transportation has made great strides in recent years (Brown et al., 2016; Doorley et al., 2015; Mueller et al., 2015). Overall, findings show that health benefits from physical activity through active transportation are substantial, and generally outweigh risks. However, a number of methodological limitations remain, often driven by available data, more so than a lack of know-how (Doorley et al., 2015; Götschi et al., 2016, 2015b; Mueller et al., 2015).

The aim of the T-MAP health impact calculation was to apply state of the art methods and expand the scope of health impact modeling within the context of health impacts of trail use in the US.

## 2. Methodology

The development of the T-MAP methodology focused on addressing three common limitations of health impact studies:

First, health impact studies predominantly focus on mortality and years of life lost, or a combination of mortality and disease impacts, such as disability adjusted life years (DALYs) (IHME, 2013). However, there is an increasing interest in assessing more short term effects on specific diseases independent of mortality.

Second, Value of Statistical Life (VSL) is a commonly used measure to value (avoided) deaths, years of life lost, or DALYs in transport and environmental appraisals (Lindhjem et al., 2016; US Department of Transportation, 2015). However, VSL is based on willingness-to-pay and produces high monetary values that are difficult to relate to tangible savings in spending (i.e. transportation budgets, infrastructure costs, health care costs, etc.). On the other hand, assessments of treatment costs or health care savings provide more tangible, albeit less comprehensive alternatives, which results in much lower figures (e.g. Gotschi, 2011). For a review of approaches applied in health impact assessments of active transportation (see Brown et al., 2016).

Third and finally, a major limitation of health impact studies of active transportation are the nature and quality of input data on walking and cycling. Robust estimates of walking or cycling are typically only available from large population surveys, which are ill suited for assessments of small areas, or of changes over time. Health impact calculations therefore usually evaluate counterfactual cases based on hypothetical scenarios (Doorley et al., 2015; Mueller et al., 2015).

Therefore in T-MAP data collection on trail activity was part of the same research effort and designed to optimize health impact modeling. And in addition to mortality outcomes, impacts on prevented disease cases were estimated and monetized using treatment costs.

### 2.1. Study setting

The T-MAP trail user intercept survey included 14 trails in 12 urban areas. The trails were selected to provide a diversity of trail types within the American urban context (see Table 1).

### 2.2. Data collection: survey and counts

Our survey included a typical travel survey adapted to the trail context, and questions related to health and physical activity. The development and testing of the survey instrument and sampling plan are described in detail elsewhere (Cohn et al., 2016). At each location, the survey was administered for a total of 24 h, segmented into eight three-hour shifts, in the summer and fall of 2015. A sampling schedule was customized for each trail based on the distribution of trail user traffic in the two weeks preceding the survey start to capture a representative sample of trail users by habitual time of day of trail use while also maximizing the survey response rate. For example, if 10% of the trail user traffic was on weekdays from 7–10 a.m., then ~10% of the survey schedule was allocated to that slot (e.g. one shift).

**Table 1**
TMAP trail data.

| Trail | City | State | Miles | Surface | Bicycle AADT | Pedestrian AADT | % Cyclists | % Weekend | SCF | Survey response rate | N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Back Cove Trail | Portland | ME | 3.6 | Paved | 176 | 738 | 19% | 58% | 1 | 67% | 218 |
| Bayshore Bikeway | San Diego | CA | 17.1 | Paved | 427 | 2339 | 15% | 51% | 1 | 50% | 171 |
| Burke-Gilman Trail | Seattle | WA | 18.8 | Paved | 1107 | 384 | 74% | 63% | 0.6 | n/a | 63 |
| Crystal City Connector | Arlington | VA | 0.4 | Paved | 517 | 509 | 50% | 50% | 1 | 34% | 407 |
| Elliott Bay Trail | Seattle | WA | 3.4 | Paved | 1236 | 2451 | 34% | 68% | 1 | n/a | 50 |
| Jefferson Davis Parkway | New Orleans | LA | 1.5 | Paved | 376 | 357 | 51% | 48% | 1 | 39% | 294 |
| Kiwanis Trail | Billings | MT | 2.1 | Paved | 30 | 132 | 19% | 48% | 1 | 87%[a] | 110 |
| Monon Trail | Indianapolis | IN | 19.7 | Paved | 1330 | 333 | 80% | 52% | 0.65 | n/a | 357 |
| M-Path | Miami | FL | 9.4 | Paved | 177 | 82 | 68% | 47% | 0.65 | 12% | 59 |
| Paseo del Nordeste Trail | Albuquerque | NM | 3.1 | Paved | 120 | 194 | 38% | 54% | 1 | 75% | 167 |
| Pikes Peak Greenway | Colorado Springs | CO | 16 | Crushed limestone | 162 | 686 | 19% | 54% | 0.55 | 42% | 161 |
| Trinity River Trail Network | Fort Worth | TX | 40 | Paved | 551 | 469 | 54% | 57% | 0.75 | 31% | 149 |
| Washington and Old Dominion Trail | Arlington | VA | 45 | Paved | 1100 | 585 | 65% | 53% | 0.55 | n/a | 397 |
| West River Parkway Trail | Minneapolis | MN | 8.9 | Paved | 916 | 450 | 67% | 56% | 0.75 | n/a | 504 |

AADT=Annual Average Daily Traffic; SCF=spatial correction factor (see Methodology 2.5.2.4.).
[a] Response rate estimate may not be reliable on this trail.

### 2.3. Background on health impact calculation

Health impact calculations use well established relationships between an exposure and an outcome from epidemiologic research (i.e. relative risks) to quantify impacts of changes in exposure in a specific population. In our case, the population is trail users, exposure is trail use (or active transportation or physical activity), and outcomes are various disease incidents, and all-cause mortality. Health impact calculation use a comparative risk assessment approach in which a relative risk is scaled to represent a specific exposure contrast – in our case, trail use vs. no trail use. This is then applied to disease or mortality risks of a population. The difference between baseline risk, and reduced risk due to trail use, applied to a specific population (i.e. number of people) produces what is referred to as health impacts.

For a more in-depth discussion of health impact calculations of active transportation (see Götschi et al., 2015a).

Defining the scope of a health impact calculation is an important first step and equally influential for the meaning of the results as are methodological aspects further down in the process.

### 2.4. Scope of the TMAP health impact calculation

#### 2.4.1. Selected pathways

This health impact calculation is limited to health benefits from physical activity gained from trail use. Trail use may also present risks, namely from exposure to air pollution and injury risk. In previous health impact studies of active transportation both air pollution and crash risks have been shown to be of less relevance compared to physical activity (Doorley et al., 2015; Mueller et al., 2015). In particular, impacts from increased exposure to air pollution due to higher ventilation rates are small, compared to benefits from physical activity, even for high pollution environments (Tainio et al., 2016). Crash data was not available for the investigated trails, however, it can be assumed that trails are safer and cleaner environments, compared to urban on-road settings typically studied in health impact studies of active transportation (Doorley et al., 2015; Mueller et al., 2015).

#### 2.4.2. Health outcomes assessed

We calculate impacts in terms of *premature deaths avoided*, monetized by *VSL*, and *prevented disease cases*, monetized as *avoided treatment costs*, because we are particularly interested in (non-fatal) health outcomes and valuations of benefits that relate with stakeholders in the health sector, and more generally, result in more tangible results.

Based on epidemiological evidence reviewed for earlier work (Götschi et al., 2015b) and publicly available data for the US we identified the following diseases as suitable for our calculation: heart disease (i.e. cardio-vascular diseases), diabetes, colon cancer, breast cancer, and depression, in addition to all-cause mortality.

## 2.5. T-MAP health impact calculation

### 2.5.1. General approach

This study uses a comparative risk assessment framework, which compares disease risk with and without trail use. The health impact calculation consists of a sequence of calculations that combine various parameters, namely epidemiologic evidence (i.e. relative risks and dose-response parameters); population data (i.e. disease and mortality rates, and treatment costs); and data on the exposure of interest (i.e. information on trail use from our own survey). Further, as part of the health impact calculation, data that initially may come in disaggregated form (i.e. per individual), or partly aggregated (i.e. means per age group) is used to produce aggregated results, e.g. average health benefits per trail.

First we describe the data used, afterwards how they were aggregated.

### 2.5.2. Data sources and preparation

*2.5.2.1. Data from epidemiologic literature. Relative risk* estimates, including corresponding exposures (i.e. "doses"), were obtained from the literature as part of earlier work (Götschi et al., 2015b) and are listed in Table 2.

*Dose-response function* is only available for physical activity and mortality (Woodcock et al., 2011). We assume that its shape applies to all outcomes associated with physical activity. Based on Woodcock et al. (2011), we fit the following dose-response function to the disease-specific relative risks to scale the protective effects resulting from trail use:

$$RR_{OBS} = 1 - RR_{EPI}^{\left(\frac{PA_{OBS}}{PA_{EPI}}\right)^{0.5}} \tag{1}$$

where $RR_{OBS}$ is the relative risk reduction (i.e. protective effect) in the local observation (i.e. in trail users); $RR_{EPI}$ is the relative risk estimate from epidemiologic literature with corresponding exposure $PA_{EPI}$, and $PA_{OBS}$ is the observed exposure (i.e. physical activity gained from trail use).

*Intensities* of trail activities, i.e. walking, bicycling and running, by various speeds, were obtained from the Compendium of Physical Activities (Ainsworth et al., 2011). Linear regressions were fit to predict intensities of trail use by speed and mode (Supplementary materials, Section 7.1).

*2.5.2.2. Population data. All-cause mortality rates* by 10-year age groups for the US-standard population were obtained from the National Vital Statistics Reports (Kochanek et al., 2012).

*Disease incidence rates* are not readily available for the US population. Instead, CDC provides rates for hospital discharges, hospital outpatient department visits, physician office visits and some other categories (CDC, 2016b). We use hospital discharge rates as the best approximation to a case definition that corresponds with epidemiologic studies, which focus on more severe cases (CDC/NCHS, 2010) (Table 2).

*2.5.2.3. Cost data. Value of Statistical Life* of $9.4 million is used to monetize avoided premature deaths (US Department of Transportation, 2015).

We use *Treatment costs* from CDC's Chronic Disease Cost Calculator (CDC, 2016c), which provides state-level estimates of medical expenditures and absenteeism costs for selected diseases by age groups for 2010. These figures include all types of treatment and prescription drugs, which is a much broader case definition than in the relative risks and the hospital discharge rates we use. We therefore approximate cost estimates as follows:

For heart disease, the largest disease group, hospital discharges represent 21% of all cases, when counting outpatient department (11%) and physician visits (68%). Thus, we assume hospital discharges represent the 20% most severe cases, and assume this applies to all outcomes.

Consulting the distribution of US health care costs per person, the top 20% (i.e. "severe patients") are responsible for 81.2% of all costs, which corresponds to an average cost per person of $32,596 (i.e. per "severe patient"), compared to an average cost of $8149 when averaged across all persons (Stanton, 2006). In other words, the 20% most costly health care recipients cost on average 4 times more than the average person. We thus multiply average treatment costs provided by the CDC chronic disease cost calculator by this same factor of 4.

Further, disease cost estimates reflect annual costs of treatment. We multiply these with estimates of duration of treatment of 1 year for heart disease, 5 years for diabetes, 3 years for colon cancer, 4 years for breast cancer, and 10 years for depression. For details, see Supplementary materials, Section 7.2.

Finally, we inflate treatment cost estimates by 16%, reflecting inflation in US health care costs from 2010 to 2015 (Patton, 2015) (Table 3).

Further, we also use *Absenteeism costs* from CDC's Chronic Disease Cost Calculator (CDC, 2016c), which we inflate by 10%, reflecting inflation in general US consumer price index for 2010–2015.

*2.5.2.4. Trail data*

*Trail length in miles. AADT*, i.e. annual average daily trail counts obtained from continuous counters installed at one location per trail. If not available by mode (i.e. bicycles vs. pedestrians), we use mode split from the survey to estimate mode specific AADT's. In the same way, we split AADT for pedestrians between walking and running.

**Table 2**
All-cause mortality and disease incidence rates (hospital discharges).

| Outcome | Age group | Rate |
|---|---|---|
| ***All-cause mortality*** | 15–24 | 65/100,000 |
| *Deaths (all-causes)* | 25–34 | 106/100,000 |
| *RR=0.81/11 MET-hours per week* (Woodcock et al., 2011) | 35–44 | 172/100,000 |
| | 45–54 | 406/100,000 |
| | 55–64 | 860/100,000 |
| | 65–74 | 1802/100,000 |
| | 75–84 | 4648/100,000 |
| ***Heart disease*** | 15–24 | 1.4/100,000 |
| *Hospital discharges* | 25–34 | 5.1/100,000 |
| *RR=0.84/5.4 MET-hours per week* (Hamer and Chida, 2008) | 35–44 | 17.3/100,000 |
| | 45–54 | 54.4/100,000 |
| | 55–64 | 125.1/100,000 |
| | 65–74 | 264.4/100,000 |
| | 75–84 | 741.9/100,000 |
| ***Diabetes*** | 15–24 | 0.3/100,000 |
| *Hospital discharges* | 25–34 | 1.2/100,000 |
| *RR=0.83/5.6 MET-hours per week* (Jeon et al., 2007) | 35–44 | 3.7/100,000 |
| | 45–54 | 10.4/100,000 |
| | 55–64 | 25.5/100,000 |
| | 65–74 | 52.7/100,000 |
| | 75–84 | 112.1/100,000 |
| ***Colon cancer*** | 15–24 | 0/100,000 |
| *Hospital discharges* | 25–34 | 0.2/100,000 |
| *RR=0.83/23.7 MET-hours per week* (Harriss et al., 2009) | 35–44 | 0.8/100,000 |
| | 45–54 | 2.7/100,000 |
| | 55–64 | 5.9/100,000 |
| | 65–74 | 11.4/100,000 |
| | 75–84 | 23/100,000 |
| ***Breast cancer*** | 15–24 | 0/100,000 |
| *Hospital discharges* | 25–34 | 1.3/100,000 |
| *RR=0.94/3.5MET-hours per week* (Monninkhof et al., 2007) | 35–44 | 7.2/100,000 |
| | 45–54 | 20.3/100,000 |
| | 55–64 | 33.2/100,000 |
| | 65–74 | 34.1/100,000 |
| | 75–84 | 29.9/100,000 |
| ***Depression*** | 15–24 | 1.3/100,000 |
| *Hospital discharges* | 25–34 | 1.7/100,000 |
| *RR=0.96/0.8 MET-hours per week* (Paffenbarger Jr. et al., 1994) | 35–44 | 2.2/100,000 |
| | 45–54 | 2.2/100,000 |
| | 55–64 | 1.2/100,000 |
| | 65–74 | 2.9/100,000 |
| | 75–84 | 1.2/100,000 |

*Spatial correction factor:* We introduce a *spatial correction factor* to correct for spatial heterogeneity in trail use. We assume that the AADT represents a peak value on the trail and that trail use declines linearly across trail segments to reach as little as 10% of the peak value for the segment with the lowest trail use.

$$AADT_{corr} = AADT \times SCF = AADT \quad \times \quad \left( DT_{min} + \frac{(1-DT_{min})}{2} \right) \tag{2}$$

where: $AADT_{corr}$ is the corrected AADT, SCF is the spatial correction factor applied, and $DT_{min}$ is an estimate of the average daily trail count on the least frequented trail segment, measured as a fraction of AADT. Estimates for $DT_{min}$ for the T-MAP trails are listed in Table 1.

More elaborate assessments of spatial distribution of trail use, i.e. counts at multiple locations, are subject to future work (Rails-to-Trails Conservancy, 2015).

*2.5.2.5. Trail survey data.* The T-MAP trail user intercept survey provides information on trail use in terms of duration, distance, and mode, both for the actual activity on the trail, as well as the access trip to the trail. When accessed by active modes, we include the access segment in the health impact calculation. We also include the full trip distance, even if it exceeds the length of the assessed trail. The survey further includes questions about physical activity in general (i.e. baseline

**Table 3**
Treatment costs for chronic diseases by age groups (based on CDC chronic disease cost calculator average costs per treated person and year, adjusted for diseases duration and "severe case" (i.e. x 4, see Section 2.5.2.3.).

| *Disease* | *Age group* | *Annual cost per patient* | *Duration* | *Cost per case* |
|---|---|---|---|---|
| *Heart disease (CVD)* | *18–44* | *$13,758* | *1* | *$13,758* |
| | *45–64* | *$23,201* | *1* | *$23,201* |
| | *65+* | *$46,581* | *1* | *$46,581* |
| | *All* | *$32,855* | *1* | *$32,855* |
| *Diabetes* | *18–44* | *$11,274* | *5* | *$56,369* |
| | *45–64* | *$16,683* | *5* | *$83,415* |
| | *65+* | *$34,154* | *5* | *$170,769* |
| | *All* | *$23,065* | *5* | *$115,323* |
| *Colon cancer* | *18–44* | *$16,175* | *3* | *$48,526* |
| | *45–64* | *$29,806* | *3* | *$89,418* |
| | *65+* | *$54,305* | *3* | *$162,914* |
| | *All* | *$40,895* | *3* | *$122,686* |
| *Breast cancer* | *18–44* | *$16,175* | *4* | *$64,702* |
| | *45–64* | *$29,806* | *4* | *$119,225* |
| | *65+* | *$54,305* | *4* | *$217,218* |
| | *All* | *$40,895* | *4* | *$163,582* |
| *Depression* | *18–44* | *$7058* | *10* | *$70,585* |
| | *45–64* | *$11,972* | *10* | *$119,723* |
| | *65+* | *$27,000* | *10* | *$270,000* |
| | *All* | *$13,166* | *10* | *$131,662* |

physical activity), trail use frequency (summer and winter), potential alternative activities if subjects would not have used the trail, as well as age and gender to fine tune the health impact calculation (see Supplementary materials for full T-MAP Intercept Survey, p. 12 or Section 7.3.).

### *2.5.3. Health impact calculation steps*

*2.5.3.1. Calculating long term physical activity from trail use.* From survey data on *distance* and *duration*, we calculate *speed*. To remove unrealistic values due to propagation of errors in distance and duration estimates, values for speed were capped at the 90th percentile, namely at 29 km/h for cycling, 14 km/h for running, and at 12 km/h for walking.

Using mode specific extrapolation formulas for intensity (see Supplementary materials p. 10 or Supplementary materials, Section 7.1).), we predict *intensity of trail activity* (measured in MET, Metabolic Equivalent of Task) based on speed. MET values were also capped at the 90th percentile.

Intensity of the trail activity is then multiplied by duration to receive *physical activity of the trail visit*, measured in MET-hours. If mode to access the trail was the same (active) mode as the trail activity itself, the time accessing the trail was added to the trail activity.

Long term physical activity behavior is typically measured in average MET-hours per week. We use the average of trail use frequency in summer and winter to scale physical activity from the observed trail visit to obtain an estimate of *annual average physical activity from trail use per week*, measured in MET-hours/week.

We also asked respondents about how likely they would have engaged in other exercise if they had not visited the trail. Based on their responses we create *substitution probabilities* (very likely=0.8; likely=0.6; undecided=0.4; unlikely=0.2; very unlikely=0), by which we discount their physical activity from trail use, to obtain *net physical activity from trail use.* We use net physical activity as a sensitivity measure in comparison to all (gross) physical activity from trail use.

Health benefits do not solely depend on how much exercise people get from trail visits, but also on their general level of physical activity (i.e. baseline physical activity). People who are less active will benefit more from the same amount of trail activity than people who already pursue very active lifestyles. To assess respondents' baseline physical activity, they were asked on how many days in a typical week they were moderately active for at least 30 min (Wanner et al., 2014). For each reported active day we accounted 2 MET-hours (equivalent to 30 min of moderate physical activity) towards their *baseline physical activity level*.

*2.5.3.2. Calculating health benefits from long term trail use per 100,000 trail users.* The relative risk reduction from regular trail use is calculated using a comparative risk assessment formula, which basically scales the relative risk from the epidemiologic literature to subjects' physical activity levels with and without trail use. The resulting difference is the *risk reduction attributable to trail use*.

$$RR_{TU}=1-\left(-1\left(\left(RR_{EPI}^{\left(\frac{(PA_{BL}+PA_{TU})}{PA_{EPI}}\right)^{0.5}}\right)-\left(RR_{EPI}^{\left(\frac{PA_{BL}}{PA_{EPI}}\right)^{0.5}}\right)\right)\right) \tag{3}$$

where $RR_{TU}$ is the relative risk reduction (i.e. protective effect) resulting from trail use, $RR_{EPI}$ is the relative risk estimate from epidemiologic literature with corresponding exposure $PA_{EPI}$, $PA_{BL}$ is the baseline exposure in the trail users (i.e. physical activity level without trail use), and $PA_{TU}$ is the exposure contrast due to trail use (i.e. physical activity gained from trail use).

The relative risk estimates from the epidemiologic literature are listed in Table 2.

The resulting risk reductions due to regular trail use are then applied to the corresponding baseline disease and mortality risks (Table 2).

$$AC_{out} = IR_{out} - IR_{out} \times RR_{TU} \tag{4}$$

where $AC_{out}$ are avoided cases of a specific outcome, per 100'000 trail users, $IR_{out}$ is the baseline risk (incidence rate) of that outcome, and $RR_{TU}$ is the risk reduction resulting from trail use for that same outcome.

This provides us with estimates of health benefits per 100,000 trail users. This format may be of use public health advocates that aim to reach out to potential trail users, for example as part of a health promotion campaign. However, for planners and decision makers who would like to assess the value of a specific trail, or trail project, benefit rates based on trail counts may be more useful.

*2.5.3.3. Calculating health benefits from long term trail use per 1000 trail counts (AADT).* Converting users to counts (or vice versa): To extrapolate health benefits from individuals (i.e. per 100,000 trail users per year) to trails we use AADT (annual average daily trail counts) obtained from continuous counters installed at one location per trail. The conversion from AADT to trail users requires a number of "corrections":

$$TU_{mode} = AADT_{mode} \times U_a/C_d = AADT_{mode} \times \frac{365\times\frac{TL}{Dist_{mean}} \times SCF}{Loops \times Freq_{week}\times 52} \tag{5}$$

where $TU_{mode}$ is the number of trail users by mode and year; AADT is the annual average daily trail count by mode; $U_a/C_d$ is the annual users to daily counts ratio; 365 is the factor to obtain an estimate per year; TL is the trail length, which is divided by $Dist_{mean}$, the average distance of a trail visit (as such, this accounts for the trail segment covered by a single counter. Not applied if $Dist_{mean} > TL$); SCF is the spatial correction factor taking into account spatial heterogeneity of trail use; Loops accounts for the proportion of trail visits that are return trips (a factor between 1 and 2); $Freq_{week}$ is the average weekly frequency of trail visits per user, and 52 is a correction factor to obtain annual frequency.

Health impact rates per 100,000 users are divided by the users-to-counts ratio ($U_a/C_d$) and divided by 100 to obtain rates per 1000 AADT. These estimates are then scaled to a trail length of 10 miles, based on the average length of trail visits (i.e. 9.4 miles) and the proportion of loop trips (78%) in our sample.

*2.5.3.4. Calculating health benefits from long term trail use for specific trails.* To quantify the health benefits for specific trails, the trail specific AADT's are multiplied with the users-to-counts ratio ($U_a/C_d$) and the rates per 100,000 trail users, divided by 100,000.

*2.5.3.5. Monetization of health benefits.* To obtain monetized health impacts, avoided premature deaths are multiplied with the VSL and avoided disease cases are multiplied by annual treatment costs and disease duration, and by annual absenteeism cost and disease duration, respectively.

### *2.5.4. Aggregation of data throughout the health impact calculation*

Trail survey data is unique for each trail user surveyed, while disease and mortality risks, and treatment costs are averaged by age groups, and yet some other parameters represent global averages per mode or trail attributes that apply to all trail users equally. As part of the calculation these different levels of aggregation need to be harmonized and aggregated to the format of the final results. Because of many non-linearities in the calculation and data, the method of aggregation has an influence on the final estimates. Most influential are the correlations of age with key parameters, such as baseline disease risks, trail use and physical activity.

At which point in the calculation data should be aggregated is not obvious, a priori. Keeping data disaggregated maintains a more realistic reflection of the distribution and individual-level combinations of attributes. However, calculations using disaggregate data are susceptible to outliers and propagation of errors, which are smoothed over by aggregating the data. Throughout the calculation we therefore apply three parallel approaches to calculate health impacts:

A. *Disaggregate approach* Keep data disaggregated for as long as possible, such as aggregate only at the end of the calculation to obtain final estimates.

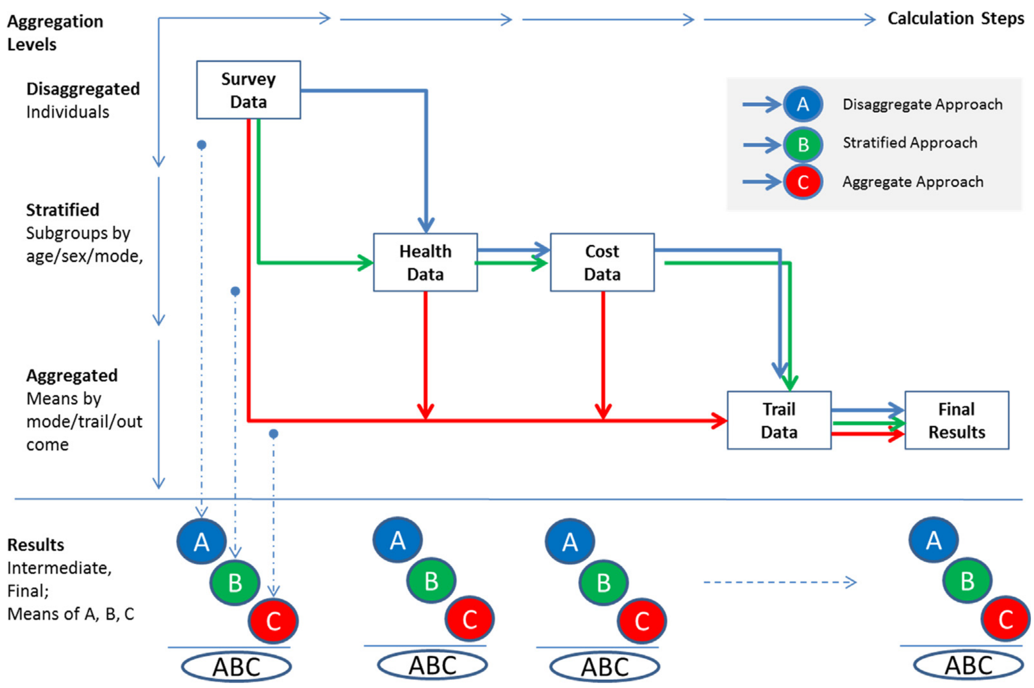


**Fig. 1.** Data aggregation approaches applied in the T-MAP health impact calculation.

B. *Stratified approach* Aggregate data immediately to subgroups defined by combining gender, age groups, and activity (mode). Aggregate estimates for subgroups at the end of the calculation to obtain final estimates.
C. *Aggregate approach* Aggregate data immediately to means for the entire trail user population (independent of age and gender; but stratified by activity). Run calculation to obtain final estimates without any further aggregation.

Fig. 1 illustrates the concept. Findings are somewhat sensitive to which approach is taken, final estimates are therefore presented as the average of the three approaches, with the lowest and highest estimate reported as percent deviation from the mean.

## 3. Results

### 3.1. Trail and trail user characteristics

Across 14 trails surveyed, 5922 trail users were approached, of which 3169 agreed to participate in the on-site survey (53%), 413 preferred to fill out an online survey (7%, not included in this analysis), and 2340 (40%) declined to participate. On 6 trails, non-participants were not recorded reliably. Excluding these, average response rate was 40%. 3107 participants provided valid surveys. Sample distribution across trails is shown in Table 1, along with other trail attributes. In total, the trails span a length of almost 200 miles, and see an average of over 500 cyclists and 700 pedestrians every day.

Descriptive statistics of the survey participants are shown in Table 4, a comprehensive summary is available in Supplementary Table 1. The surveyed trail users were on average 45 years old, in the majority male (58%) and predominantly cyclists (53%). The average time spent on a trail was just over an hour, and in summer, half of all users frequented the trail three times per week (in winter 30%). The trail users reported to be in good to excellent health, and to be generally very active (80% report 4 or more active days per week). The vast majority of trail use was for recreational purposes (77%), as compared to 22% utilitarian (i.e. transportation).

### 3.2. Health impacts of trail use

Our health impact analysis produces a wealth of results. Besides the main results presented here, more detailed tables are available as part of Supplementary materials. All estimates are per year.

Regular trail use reduces disease risks between 7 and 13% in the surveyed population. Mortality risk is reduced by 11% (Supplementary Table 2).

Regular trail use prevents 36 hospitalizations, and about $2.1 million, due to the five assessed chronic diseases per 100,000 trail users and year (Table 5). The majority of these are attributable to heart disease (28 cases, and $985,000/100,000 × year; Supplementary Table 3). Cost savings due to prevented absenteeism (i.e. days missed at work) are much

**Table 4**
TMAP trail user intercept survey descriptive statistics.

| *Variable* | *Category* | *Value* | *Confidence interval (95%)* | *N* |
|---|---|---|---|---|
| *Duration of activity (min; incl. access if same mode as on trail)* | | *71.05* | *(69–73.1)* | *3150* |
| *Distance (miles, incl. access)* | | *10.99* | *(10.53–11.45)* | *3149* |
| *Age* | | *45.07* | *(44.55–45.59)* | *3150* |
| *Gender* | | | | *3149* |
| | *Female* | *42%* | *(40–43%)* | *1323* |
| | *Male* | *58%* | *(57–60%)* | *1826* |
| *Trail activity (mode)* | | | | *3132* |
| | *Bike* | *53%* | *(51–55%)* | *1660* |
| | *Walk* | *31%* | *(29–32%)* | *971* |
| | *Run* | *16%* | *(14–8%)* | *501* |
| | *Other* | *1%* | *(0–10%)* | *31* |
| *Trail use summer* | | | | *3150* |
| | *More than 3 times per week* | *53%* | *(51–55%)* | *1669* |
| | *2–3 times per week* | *22%* | *(20–4%)* | *693* |
| | *Once a week* | *9%* | *(7–1%)* | *284* |
| | *2–3 times a month* | *5%* | *(4–7%)* | *158* |
| | *Once a month* | *4%* | *(2–6%)* | *126* |
| | *Less than once a month* | *3%* | *(2–6%)* | *94* |
| | *Never* | *5%* | *(3–7%)* | *158* |
| *Physically active days per week* | | | | *3120* |
| | *0* | *1%* | *(0–%)* | *31* |
| | *1* | *2%* | *(1–2%)* | *62* |
| | *2* | *4%* | *(3–4%)* | *125* |
| | *3* | *12%* | *(12–12%)* | *374* |
| | *4* | *16%* | *(16–16%)* | *499* |
| | *5* | *24%* | *(24–25%)* | *749* |
| | *6* | *16%* | *(16–16%)* | *499* |
| | *7* | *25%* | *(25–26%)* | *780* |
| *Health status* | | | | *3150* |
| | *Excellent* | *34%* | *(32–6%)* | *1071* |
| | *Very good* | *40%* | *(38–42%)* | *1260* |
| | *Good* | *22%* | *(20–24%)* | *693* |
| | *Fair* | *4%* | *(3–6%)* | *126* |
| | *Poor* | *0%* | *(0–23%)* | *0* |

smaller at approx. $25,000 per 100,000 trail users and year (Supplementary Table 6).

Converted to rates per trail counts, every year, one chronic disease case is prevented for approx. every 13 miles of trail with an AADT of 1,000, equivalent to annual treatment cost savings of $59,000.

On average, cycling makes up for almost half (46%), walking for one third (33%) and running for one fifth (21%) of all health impacts, although these splits vary considerably across the T-MAP trails.

Naturally, estimates for mortality are substantially higher. The case definition, and therefore the underlying all-cause mortality risk is much broader, compared to hospital discharges, and VSL is much higher than even the most expensive treatment costs per case. Regular trail use prevents 182 premature deaths, valued at about $1.7 billion, per 100'000 trail users every year (Table 6). Every 2.6 miles of trail with an AADT of 1,000 prevent one premature death per year, or $9.4 million in terms of VSL.

The majority of trail users state that they would engage in other physical activities, if they had not been able to visit the trail (47% very likely, 25% likely). Based on the substitution probabilities assigned to these categories, on average 57% of trail activity would have been substituted by other exercise. In other words, every hour of trail use only leads to a net gain of 26 min of physical activity. Accordingly, health impacts based on net physical activity gained from regular trail use are 19 prevented disease cases or $1,085,000 in saved treatment costs, and 95 premature deaths avoided valued at $893 million, all per 100,000 trail users. Additional results for net gain in physical activity are available in Supplementary Table 4 and Supplementary Table 5.

Comparisons across the three aggregation approaches applied (disaggregate, stratified, aggregate) reveal that results can be quite sensitive to the chosen approach (Supplementary Table 6). For bicycling the stratified analysis yields the highest estimates, although all three approaches are within a narrow range of $\pm$10%. For walking and running, however, the aggregate approach leads to estimates as much as 70% higher than the mean of all three, and more than twice as high than disaggregate or stratified approaches.

**Table 5**
Health impacts from trail use for all diseases combined (avoided hospital cases and treatment costs, per year).

| *Hospital cases, treatment costs* | | *All modes* | | *Bicycling* | | | | *Walking* | | | | *Running* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Impact measure/ Trail*** | ***Trail length (miles)*** | ***Avoided cases*** | ***Avoided costs*** | ***AADT Bike*** | ***Avoided cases*** | ***Avoided costs*** | ***Range %*** | ***AADT Walk*** | ***Avoided cases*** | ***Avoided costs*** | ***Range %*** | ***AADT Run*** | ***Avoided cases*** | ***Avoided costs*** | ***Range %*** |
| *Estimates per 100,000 trail users* | | *36.18* | *$2,113,411* | | *13.83* | *$856,958* | *−13,+11* | | *11.21* | *$700,823* | *−17,+30* | | *11.14* | *$555,630* | *−33,+58* |
| *Estimates per trail count of 1000 (AADT)* | *10* | *0.82* | *$48,261* | | *0.36* | *$22,311* | *−13,+11* | | *0.25* | *$15,807* | *−16,+27* | | *0.21* | *$10,143* | *−33,+58* |
| *Back Cove Trail* | *3.6* | *0.22* | *$13,150* | *176* | *0.02* | *$940* | *−21,+34* | *844* | *0.16* | *$10,482* | *−10,+6* | *243* | *0.04* | *$1,728* | *−27,+37* |
| *Bayshore Bikeway* | *17.1* | *1.60* | *$77,433* | *427* | *0.21* | *$12,660* | *−5,+6* | *2380* | *0.65* | *$19,822* | *−75,+148* | *1444* | *0.74* | *$44,951* | *−41,+60* |
| *Burke Gilman Trail* | *18.8* | *0.18* | *$10,811* | *1107* | *0.12* | *$7,243* | *−10,+8* | *433* | *0.04* | *$2,446* | *−17,+29* | *268* | *0.02* | *$1,122* | *−45,+81* |
| *Crystal City Connector*[a] | *0.4* | *0.15* | *$7,813* | *517* | *0.05* | *$2,567* | *−8,+9* | *602* | *0.05* | *$3,112* | *−11,+15* | *451* | *0.04* | *$2,134* | *−21,+32* |
| *Elliott Bay Trail* | *3.4* | *0.76* | *$45,398* | *1236* | *0.08* | *$3,929* | *−23,+32* | *2892* | *0.53* | *$34,592* | *−6,+8* | *1153* | *0.15* | *$6,877* | *−32,+49* |
| *Jefferson Davis Parkway* | *1.5* | *0.04* | *$1,992* | *376* | *0.02* | *$868* | *−9,+9* | *391* | *0.02* | *$868* | *−15,+27* | *158* | *0.01* | *$256* | *−37,+50* |
| *Kiwanis Trail* | *2.1* | *0.04* | *$2,814* | *30* | *0.01* | *$377* | *−28,+19* | *148* | *0.03* | *$2,032* | *−22,+39* | *54* | *0.01* | *$405* | *−41,+70* |
| *M-Path* | *9.4* | *0.03* | *$1,536* | *177* | *0.02* | *$1,162* | *−10,+15* | *86* | *0.01* | *$322* | *−31,+38* | *11* | *0.00* | *$52* | *−27,+55* |
| *Monon Trail* | *19.7* | *0.17* | *$10,317* | *799* | *0.09* | *$5,647* | *−15,+15* | *536* | *0.05* | *$2,733* | *−24,+44* | *324* | *0.03* | *$1,937* | *−32,+50* |
| *Paseo Del Nordeste Trail* | *3.1* | *0.07* | *$4,559* | *120* | *0.02* | *$1,469* | *−17,+14* | *209* | *0.04* | *$2,776* | *−27,+49* | *46* | *0.01* | *$314* | *−42,+82* |
| *Pikes Peak Greenway* | *16* | *0.25* | *$16,318* | *162* | *0.02* | *$1,465* | *−28,+19* | *946* | *0.11* | *$8,205* | *−11,+19* | *1211* | *0.12* | *$6,648* | *−27,+46* |
| *Trinity River Trail Network* | *40* | *0.35* | *$19,051* | *551* | *0.20* | *$11,320* | *−15,+9* | *542* | *0.09* | *$5,173* | *−16,+29* | *432* | *0.06* | *$2,558* | *−49,+96* |
| *Washington & Old Dominion Trail* | *45* | *0.43* | *$26,291* | *1100* | *0.27* | *$17,523* | *−27,+18* | *765* | *0.07* | *$4,622* | *−19,+32* | *1029* | *0.09* | *$4,146* | *−32,+61* |
| *West River Parkway Trail* | *8.9* | *0.29* | *$17,777* | *916* | *0.17* | *$10,944* | *−13,+11* | *487* | *0.08* | *$4,973* | *−29,+56* | *249* | *0.04* | *$1,860* | *−45,+86* |

[a] Note: impacts based on reported trip distance including trail-activities beyond trail length of 0.4 miles.

**Table 6**
Health impacts from trail use for all-cause mortality (avoided premature deaths, VSL, per year).

| *All-cause mortality, VSL* | | *All modes* | | *Bicycling* | | | | *Walking* | | | | *Running* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Impact measure/Trail* | *Trail length (miles)* | *Avoided cases* | *Avoided costs* | *AADT Bike* | *Avoided cases* | *Avoided costs* | *Range%* | *AADT Walk* | *Avoided cases* | *Avoided costs* | *Range%* | *AADT Run* | *Avoided cases* | *Avoided costs* | *Range%* |
| Estimates per 100,000 trail users | | 182.23 | $1,712,989,760 | | 69.44 | $652,754,752 | −13,+11 | | 55.03 | $517,252,352 | −16,+27 | | 57.76 | $542,982,656 | −36,+64 |
| Estimates per trail count of 1000 (AADT) | 10 | 4.12 | $38,742,313 | | 1.81 | $17,026,330 | −14,+11 | | 1.24 | $11,665,611 | −14,+24 | | 1.07 | $10,050,372 | −36,+64 |
| Back Cove Trail | 3.6 | 1.06 | $9,945,611 | 176 | 0.08 | $797,061 | −22,+38 | 844 | 0.78 | $7,356,313 | −13,+7 | 243 | 0.19 | $1,792,237 | −33,+49 |
| Bayshore Bikeway | 17.1 | 8.09 | $76,031,536 | 427 | 1.07 | $10,046,352 | −6,+6 | 2380 | 3.33 | $31,288,424 | −82,+161 | 1444 | 3.69 | $34,696,760 | −42,+61 |
| Burke Gilman Trail | 18.8 | 0.92 | $8,673,290 | 1107 | 0.61 | $5,696,000 | −8,+7 | 433 | 0.20 | $1,899,346 | −15,+25 | 268 | 0.11 | $1,077,944 | −43,+76 |
| Crystal City Connector[a] | 0.4 | 0.77 | $7,241,530 | 517 | 0.25 | $2,358,024 | −8,+9 | 602 | 0.28 | $2,637,182 | −10,+13 | 451 | 0.24 | $2,246,324 | −22,+34 |
| Elliott Bay Trail | 3.4 | 3.77 | $35,409,969 | 1236 | 0.44 | $4,104,150 | −25,+38 | 2892 | 2.55 | $23,941,838 | −4,+4 | 1153 | 0.78 | $7,363,981 | −38,+63 |
| Jefferson Davis Parkway | 1.5 | 0.23 | $2,118,577 | 376 | 0.09 | $821,264 | −9,+10 | 391 | 0.10 | $907,193 | −16,+28 | 158 | 0.04 | $390,120 | −36,+48 |
| Kiwanis Trail | 2.1 | 0.22 | $2,021,904 | 30 | 0.03 | $263,411 | −32,+21 | 148 | 0.15 | $1,380,694 | −21,+37 | 54 | 0.04 | $377,799 | −46,+81 |
| M-Path | 9.4 | 0.13 | $1,223,611 | 177 | 0.10 | $905,240 | −9,+14 | 86 | 0.03 | $266,722 | −31,+38 | 11 | 0.01 | $51,649 | −34,+67 |
| Monon Trail | 19.7 | 0.89 | $8,400,988 | 799 | 0.48 | $4,513,007 | −14,+14 | 536 | 0.23 | $2,172,504 | −24,+45 | 324 | 0.18 | $1,715,477 | −31,+47 |
| Paseo Del Nordeste Trail | 3.1 | 0.36 | $3,408,401 | 120 | 0.12 | $1,135,289 | −15,+12 | 209 | 0.21 | $1,929,551 | −28,+51 | 46 | 0.04 | $343,561 | −50,+99 |
| Pikes Peak Greenway | 16 | 1.22 | $11,442,087 | 162 | 0.11 | $1,025,827 | −29,+19 | 946 | 0.52 | $4,918,837 | −3,+5 | 1211 | 0.58 | $5,497,423 | −31,+55 |
| Trinity River Trail Network | 40 | 1.78 | $16,750,480 | 551 | 1.00 | $9,420,313 | −14,+9 | 542 | 0.44 | $4,098,649 | −11,+20 | 432 | 0.34 | $3,231,518 | −51,+99 |
| Washington & Old Dominion Trail | 45 | 2.14 | $20,125,024 | 1100 | 1.34 | $12,570,692 | −28,+19 | 765 | 0.36 | $3,409,600 | −17,+28 | 1029 | 0.44 | $4,144,732 | −36,+69 |
| West River Parkway Trail | 8.9 | 1.42 | $13,363,887 | 916 | 0.82 | $7,716,663 | −14,+11 | 487 | 0.39 | $3,711,933 | −30,+58 | 249 | 0.21 | $1,935,291 | −49,+95 |

[a] Note: impacts based on reported trip distance including trail-activities beyond trail length of 0.4 miles.

## 4. Discussion and conclusions

The T-MAP trail intercept survey is an unprecedented effort into understanding urban trail use behavior, both in its scope and detail. The health impact modeling methodology developed for this project benefited in several ways from the tailored survey and count efforts (Cohn et al., 2016; Lindsey et al., 2016). In particular, the calculation goes beyond state-of-the-art by considering individual level data on trail use, such as derived speed and intensity of activity; more realistic estimates of long term behavior based on summer and winter frequency of use; and the assessment of baseline physical activity and possible substitution behavior. Modeling prevented disease cases and avoided treatment costs provides a tangible alternative to mortality-based outcomes which are usually monetized based on VSL. Our parallel calculations using disaggregated, stratified and aggregated data provide methodological insights of relevance to health impact modeling beyond trail use.

Survey respondents consist of a very active population. Summing up self-reported trail use and general physical activity (active days) suggests that 87% fulfill WHO's recommendations of physical activity (WHO, 2010). Based on active days alone, only 42% achieve this benchmark, but this is still twice as many than in the general US population (CDC, 2016a).

The reduction in health risks that trail users achieve through regular trail use, around 10%, is substantial. It is important to note, however, that if inactive persons would start to engage in a similar level of trail use, their benefits would be considerably higher (risk reduction of 25%), due to the non-linear relationship between physical activity and health.

To put the benefits from physical activity from trail use in perspective, we compare them with another important public health topic, air pollution, which affects similar health outcomes. To achieve mortality benefits similar to those from trail use through a reduction in air pollution exposure, one would have to move from one of the most polluted US cities ($PM_{2.5} \sim 20\ \mu g/m^3$) to a place with basically no air pollution (Hoek et al., 2013; WHO, 2016).

Our estimates of savings in treatment costs add a tangible dimension to the quantification of benefits from trails. Nonetheless, and despite a number of refinements of our methods compared to earlier health impact calculations (Brown et al., 2016), these figures need to be interpreted with caution.

Carlson et al. (2015) have estimated that annual health care expenditure is about $1,400 less in active adults ($>150$ minutes of moderate physical activity per week), compared to inactive adults. Despite a comparable contrast in physical activity in the trail users surveyed (compared to no trail use), we estimated savings in treatment costs for trail users of only $11–$21 per capita and year. We consider several reasons that could explain this discrepancy.

First of all, our assessment is limited to hospital discharge rates. In combination with the limited selection of outcomes, these only capture an unknown fraction of all healthcare costs. However, for some diseases, like cardio-vascular disease or diabetes, multiple hospitalizations per year may inflate the disease rates relative to the corresponding cost data, which is per year.

Secondly, we investigate a relatively young population. 90% of trail users are less than 65 years old. Average health care expenses are more than three times higher in elderly (Keehan et al., 2004). In our calculation, this age effect manifests itself both in terms of baseline diseases risks and treatment costs per case. Baseline disease risks among 65–74 year olds are about 15 times higher for heart disease, colon cancer and diabetes, and about 5 times higher for breast cancer, compared to 35–44 year olds. Disease risk rates for depression are similar across age groups. Treatment costs per case in patients 65 years and older are about three to five times higher than in those 18–44 years old. We estimate that the combination of lower disease rates and lower costs per case explain about half of the difference between avoided treatment costs in our sample compared to total health care cost savings in active vs. inactive subjects of a representative population sample, as observed by Carlson et al. (2015). For similar reasons, absentee costs are extremely low, although, these may in addition be deflated by less severe cases, which we did not correct for. Our calculation does not account for any lag effects between current physical activity and health benefits later in life. Although physiologically highly plausible, epidemiologic evidence is still limited to quantify such considerations.

Thirdly, methodological decisions, assumptions, and uncertainties certainly lead to discrepancies in any comparison with other studies. Some uncertainty to self-reported data is inherent. In the context of our health impact calculation the potential influence of misclassification of physical activity variables is noteworthy, although difficult to assess. In contrast to previous studies, we directly asked subjects to report not only on the activity of interest (i.e. trail use) but also on their usual level of physical activity (baseline physical activity) and there likelihood to substitute trail use with another form of exercise allowing us to assess net-gains in physical activity. Conceptually both baseline activity levels and consideration of substitution behavior should improve estimates of health benefits from trail use, but all three physical activity items represent desirable behaviors which are prone to over-reporting. Over-estimation of trail use will inflate benefits, while over-estimation of baseline activity and substitution will deflate benefits. In our survey, trail use is the only actually revealed behavior and is captured in fairly easily recalled concepts of self-reported duration, distance, and frequency, while baseline activity and substitution behavior are more hypothetical and challenging to respondents, plus we need to make some assumptions to quantify these, which introduces an additional source of misclassification.

We also had to take various assumptions throughout the calculation to address the lack of or incompatibility of data, namely matching different definitions of age groups, and stratifying overall disease rates applying age distributions from disease-specific mortality rates. We do not expect our estimates to be sensitive to assumptions at this level of detail. However, aligning varying case definitions between epidemiological findings, publically available disease rates, and treatment cost data remains a source of uncertainty of unknown magnitude.

Arguably our most arbitrary assumptions relate to the spatial correction factor for heterogeneity in trail use along trails, which we chose to take without any empirical grounds (other than the anecdotal reports that automated counters tend to be installed at highly frequented locations). In applying spatial correction factors based on very crude assumptions we err on the conservative side. Not applying any spatial correction factors would have led to approximately 25% higher estimates. To base spatial correction on empirical data in the future, as part of T-MAP we developed the smartphone-based count app "GoCounter" (Rails-to-Trails Conservancy, 2015), which facilitates efficient count data collection at numerous locations. An online calculator to extrapolate short term counts to annual means is also part of the T-MAP tool box (Rails-to-Trails Conservancy, 2016). Trails of course are fairly simple, linear objects to assess spatial heterogeneity. Implementing the same concept for active transportation more broadly would call for area-wide active transportation demand models (Kuzmyak et al., 2014).

Our calculation provides some long sought insights on the sensitivity of health impact estimates with regards to level of data aggregation. Aggregate calculation approaches, such as for example WHO's HEAT tool (Cavill et al., 2012), are practice-friendly because of their minimal data requirements, whereas disaggregate or stratified approaches, such as ITHIM (Woodcock, 2014), promise more accurate estimates at a considerable cost in user burden. Our calculation suggests that aggregate approaches may overestimate impacts considerably compared to stratified approaches. The disaggregate approach, however, produced very similar estimates as the stratified approach. However, these differences are noticeably less pronounced for cycling, possibly because cycling in our sample is a more homogenous behavior. Without further exploration of these findings it seems fair to suggest that health impact calculation should aspire to stratify by age.

As such our study demonstrated that tailored data collection can substantially improve health impact calculations, but additional work is needed to refine our approach. In particular, a more comprehensive approach to quantifying impacts on health care costs, including further harmonization of underlying disease incidence and treatment cost data, is warranted. T-MAP intends to develop a practice-friendly platform to facilitate intercept surveys and health impact calculations in the future.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jth.2017.01.005.

## References

Ainsworth, B.E., Haskell, W.L., Herrmann, S.D., Meckes, N., Bassett Jr., D.R., Tudor-Locke, C., Greer, J.L., Vezina, J., Whitt-Glover, M.C., Leon, A.S., 2011. 2011 Compendium of Physical Activities: a second update of codes and MET values. Med. Sci. Sport Exerc. 43, 1575–1581, http://dx.doi.org/10.1249/MSS.0b013e31821ece12.

Brown, V., Diomedi, B.Z., Moodie, M., Veerman, J.L., Carter, R., 2016. A systematic review of economic analyses of active transport interventions that include physical activity benefits. Transp. Policy 45, 190–208, http://dx.doi.org/10.1016/j.tranpol.2015.10.003.

Buehler, R., Pucher, J., Merom, D., Bauman, A., 2011. Active travel in Germany and the U.S. Contributions of daily walking and cycling to physical activity. Am. J. Prev. Med. 41, 241–250, http://dx.doi.org/10.1016/j.amepre.2011.04.012.

Buehler, R., Götschi, T., Winters, M., 2016. Moving toward active transportation: how policies can encourage walking and bicycling. Act. Living Res., 1–8.

Carlson, S.A., Fulton, J.E., Pratt, M., Yang, Z., Adams, E.K., 2015. Inadequate physical activity and health care expenditures in the United States. Prog. Cardiovasc. Dis. 57, 315–323, http://dx.doi.org/10.1016/j.pcad.2014.08.002.

Cavill, N., Kahlmeier, S., Dinsdale, H., Gotschi, T., Oja, P., Racioppi, F., Rutter, H., 2012. The Health Economic Assessment Tool (HEAT) for walking and cycling: from evidence to advocacy on active transport. J. Sci. Med. Sport Conf., S69.

CDC, 2016a. Facts about Physical Activity WWW Document. URL : ⟨https://www.cdc.gov/physicalactivity/data/facts.htm⟩.

CDC, 2016b. FastStats - Statistics by Topic WWW Document. URL : ⟨https://www.cdc.gov/nchs/fastats/⟩.

CDC, 2016c. Chronic Disease Cost Calculator Version 2 WWW Document. URL : ⟨www.cdc.gov/chronicdisease/calculator⟩.

CDC/NCHS, 2010. National Hospital Discharge Survey WWW Document. URL : ⟨http://www.cdc.gov/nchs/data/nhds/2average/2010ave2_firstlist.pdf⟩.

Cohn, J., Hadden-Loh, T., Götschi, T., 2016. Development of a survey tool to quantify health impacts of trail use. J. Park Recreat. Admi. 34, 36–51.

Doorley, R., Pakrashi, V., Ghosh, B., 2015. Quantifying the health impacts of active travel: assessment of methodologies. Transp. Rev. 35, 559–582, http://dx.doi.org/10.1080/01441647.2015.1037378.

Gotschi, T., 2011. Costs and Benefits of Bicycling Investments in Portland, Oregon. J. Phys. Act. Heal. 8, S49–S58.

Götschi, T., Garrard, J., Giles-Corti, B., 2015a. Cycling as a part of daily life: a review of health perspectives. Transp. Rev., 1–27, http://dx.doi.org/10.1080/01441647.2015.1057877.

Götschi, T., Tainio, M., Maizlish, N., Schwanen, T., Goodman, A., Woodcock, J., 2015b. Contrasts in active transport behaviour across four countries: how do they translate into public health benefits?. Prev. Med., 74; 42–48, http://dx.doi.org/10.1016/j.ypmed.2015.02.009.

Götschi, T., Garrard, J., Giles-Corti, B., 2016. Cycling as a part of daily life: a review of health perspectives. Transp. Rev. 36, 45–71, http://dx.doi.org/10.1080/01441647.2015.1057877.

Hamer, M., Chida, Y., 2008. Active commuting and cardiovascular risk: a meta-analytic review. Prev. Med. 46, 9–13, http://dx.doi.org/10.1016/j.ypmed.2007.03.006.

Harriss, D.J., Atkinson, G., Batterham, A., George, K., Tim Cable, N., Reilly, T., Haboubi, N., Renehan, A.G., 2009. Lifestyle factors and colorectal cancer risk (2): a systematic review and meta-analysis of associations with leisure-time physical activity. Colorectal Dis. 11, 689–701.

Hebert, K.A., Wendel, A.M., Kennedy, S.K., Dannenberg, A.L., 2012. Health impact assessment: a comparison of 45 local, national, and international guidelines. Environ. Impact Assess. Rev. 34, 74–82, http://dx.doi.org/10.1016/j.eiar.2012.01.003.

Hoek, G., Krishnan, R.M., Beelen, R., Peters, A., Ostro, B., Brunekreef, B., 2013. Long-term air pollution exposure and cardio- respiratory mortality: a review. Environ. Heal. 12, 43, http://dx.doi.org/10.1186/1476-069X-12-43.

IHME, 2013. Global burden of disease study 2010, Report Results 1990-2010. Institute for Health Metrics and Evaluation (IHME), Seattle, United States.

Jeon, C.Y., Lokken, R.P., Hu, F.B., van Dam, R.M., 2007. Physical activity of moderate intensity and risk of type 2 diabetes: a systematic review. Diabetes Care 30, 744–752, http://dx.doi.org/10.2337/dc06-1842.

Keehan, S.P., Lazenby, H.C., Zezza, M.A., Catlin, A.C., 2004. Age estimates in the national health accounts. Health Care Financ. Rev. 26, 1–16.

Kochanek, K.D., Xu, J., Murphy, S.L., Minino, A.M., Kung, H.-C., 2012. National vital statistics reports deaths: final data for 2009. Natl. Cent. Heal. Stat. 60, 1–117. (doi:May 8, 2013).

Kuzmyak, J.R., Walters, J., Bradley, M., Kockelman, K.M., 2014. Estimating Bicycling and Walking for Planning and Project Development: A Guidebook, Report.

Lindhjem, H., Navrud, S., Braathen, N.A., 2016. Meta-analysis of Value of Statistical Life estimates WWW Document. OECD. URL : ⟨http://www.oecd.org/env/tools-evaluation/env-value-statistical-life.htm⟩.

Lindsey, G., Ermagun, A., Loh, T., 2016. The Effects of weather on urban trail use: a national study. Transp. Res. Board 95th.

Lowry, M.B., Furth, P., Hadden-Loh, T., 2016. Prioritizing new bicycle facilities to improve low-stress network connectivity. Transp. Res. Part A Policy Pract. 86, 124–140, http://dx.doi.org/10.1016/j.tra.2016.02.003.

Monninkhof, E.M., Elias, S.G., Vlems, F.A., van der Tweel, I., Schuit, A.J., Voskuil, D.W., van Leeuwen, F.E., 2007. Physical activity and breast cancer: a systematic review. Epidemiology 18, 137–157.

Mueller, N., Rojas-Rueda, D., Cole-Hunter, T., de Nazelle, A., Dons, E., Gerike, R., Götschi, T., Int Panis, L., Kahlmeier, S., Nieuwenhuijsen, M., 2015. Health impact assessment of active transportation: a systematic review. Prev. Med. 76, 103–114, http://dx.doi.org/10.1016/j.ypmed.2015.04.010.

Paffenbarger Jr., R.S., Lee, I.M., Leung, R., 1994. Physical activity and personal characteristics associated with depression and suicide in American college men. Acta Psychiatr. Scand. Suppl. 377, 16–22.

Patton, M., 2015. U.S. Health Care Costs Rise Faster Than Inflation WWW Document. Forbes. URL : ⟨http://www.forbes.com/sites/mikepatton/2015/06/29/u-s-health-care-costs-rise-faster-than-inflation/#af160246ad25⟩ (accessed 1.1.16).

Physical Activity Guidelines Advisory Committee, 2008. Physical Activity Guidelines Advisory Committee Report 2008, Report. U.S. Department of Health and Human Services, Washington, DC.

Rails-to-Trails Conservancy, 2015. Go Counter WWW Document. URL : ⟨https://itunes.apple.com/us/app/go-counter/id1069744691?Mt=8⟩.

Rails-to-Trails Conservancy, 2016. Trail Traffic Calculator WWW Document. URL : ⟨http://www.railstotrails.org/our-work/research-and-information/trail-modeling-and-assessment-platform/trail-traffic-calculator/⟩.

Stanton, M.W., 2006. The high concentration of U.S. health care expenditures. Agency Healthc. Res. Qual..

Tainio, M., de Nazelle, A.J., Götschi, T., Kahlmeier, S., Rojas-Rueda, D., Nieuwenhuijsen, M.J., de Sá, T.H., Kelly, P., Woodcock, J., 2016. Can air pollution negate the health benefits of cycling and walking? Prev. Med. http://dx.doi.org/10.1016/j.ypmed.2016.02.002.

US Department of Transportation, 2015. Economic Values Used in Analyses, Guidance on Treatment of the Economic Value of a Statistical Life in U.S. Department of Transportation Analyses.

Wanner, M., Probst-Hensch, N., Kriemler, S., Meier, F., Bauman, A., Martin, B.W., 2014. What physical activity surveillance needs: validity of a single-item questionnaire. Br. J. Sport Med. 48, 1570–1576, http://dx.doi.org/10.1136/bjsports-2012-092122.

WHO, 2016. WHO | WHO Global Urban Ambient Air Pollution Database (update 2016) WWW Document. URL : ⟨http://www.who.int/phe/health_topics/outdoorair/databases/cities/en/⟩ (accessed 7.25.16).

WHO, 2010. Global Recommendations on Physical Activity for Health, Report. World Health Organization, Geneva.

Woodcock, J., 2014. Intergrated Transport and Health Impact Modelling Tool (ITHIM). WWW Document. URL : ⟨http://www.cedar.iph.cam.ac.uk/research/modelling/ithim/⟩.

Woodcock, J., Franco, O.H., Orsini, N., Roberts, I., 2011. Non-vigorous physical activity and all-cause mortality: systematic review and meta-analysis of cohort studies. Int. J. Epidemiol. 40, 121–138, http://dx.doi.org/10.1093/ije/dyq104.